Manipulating the Shorts

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ABSTRACT

A fear of manipulative short squeezes acts as an indirect constraint on short-selling. We investigate if this fear has firm foundations, by examining a stock lending dataset for evidence of patterns consistent with manipulative short squeezes. From a sample comprising nearly half a million firm days, we find only twenty examples of manipulative patterns. We observe statistically and economically significant abnormal returns around these events. These are followed by a price reversal, but short-sellers who have covered their positions do not benefit from this effect. Market data such as volatility of stock returns, trading volume, liquidity, and stock loan fees and utilization rates might be expected to assist in anticipating manipulative short squeezes. However, it is difficult to predict manipulative short squeezes from this data alone.

Key words: short selling, stock manipulation, short squeeze

1. Introduction

Although both long and short investors can become victims of stock manipulation, short-sellers are particularly vulnerable due to the possibility of stock loan recall. When a stock loan is recalled and cannot be replaced, the short-seller must cover his position by buying stock in the market. Thus, a stock loan recall has the potential to create "forced trading", making manipulation more effective.

From a series of interviews conducted between 2004 and 2009, we find that a number of practising and prospective short-sellers fear becoming victims of manipulative short squeezes. This concern can serve to limit the extent of short-selling in a market, and so acts as an indirect constraint on short-selling. Jacobs and Levy (2007) assert that the fear of short squeezes deters some short-sellers, but that this fear is largely unfounded as short squeezes are rare events and confined to illiquid stocks. The authors do not, however, provide any evidence to back up this claim. We use data from the stock lending market to investigate their contention and to address the following research question: "should short-sellers fear manipulative short squeezes?"

Before proceeding further, it is useful to define some key terms. A 'short squeeze' is described by Dechow *et al.* (2001) as a situation where a stock loan is recalled and the stock borrower is unable to find an alternative lender. The stock borrower must then buy shares in the open market to repay the stock loan and to close the position.[1] Where a short-squeeze occurs in a highly liquid stock, short-covering would incur trading and opportunity costs, but would have little market impact. However, a short squeeze in a stock with poor liquidity could have market impact, imposing losses on the short-seller.

Stock loan recalls and short squeezes are frequently described in the literature, but are rarely researched further. One exception is D'Avolio (2002), who investigates stock loan recalls and finds that it can be difficult to re-borrow stock after a recall. He finds that 2% of stocks on loan

[1] A similar definition is offered by Duffie *et al.* (2002): "The lender may opt out of a continuing lending arrangement by issuing a recall notice, in which case the borrower must return the stock." …"In some cases, called 'short squeezes', the borrower (or its broker) is unable to locate lendable shares and is 'bought in', that is, must buy the stock outright. If the borrower fails to deliver the security in standard settlement time, the lender itself may buy it, using the cash collateral."

are recalled during an average month, and that it takes a mean of 23 days (and a median of 9 days) to replace a recalled stock loan. Where unable to replace a stock loan, a short-seller may cover his short position or default on his stock loan. Accordingly, stock loan recalls can be used to induce short-covering, thus making manipulation more effective.

Short squeezes can be classified as ‘non-manipulative’ or ‘manipulative’. A ‘non-manipulative short squeeze’ occurs naturally when a stock lender recalls his stock (say, to settle a stock sale) and the short-seller is unable to replace his stock loan, due to limited supply. By contrast, a ‘manipulative short squeeze’ is associated with deliberate recall by the stock lender as part of a broader manipulation strategy. This paper examines situations in which short-sellers become the victims of manipulative short squeezes.

The literature on security price manipulation offers insights into the characteristics of a manipulative short squeeze. According to Allen and Gale (1992), manipulation can be ‘information-based’ (spreading false rumours or using false accounting); ‘action-based’ (e.g. launching a spurious take-over bid); or ‘trade-based’ (e.g. ‘pump and dump’ trading). In the latter case, a manipulator ‘pumps up’ the share price with buying. Unable to distinguish between informed buying and manipulative buying, positive feedback traders are attracted to the rising share price and buy shares in the company, leading to further stock price increases. The manipulator then ‘dumps’ his stock at the higher price, securing a profit. There is also empirical evidence that ‘pump and dump’ manipulation can secure profits for manipulators: Khwaja and Mian (2005) study 32 months of broker trades on the Karachi Stock Exchange (KSE) and find evidence of trade-based ‘pump and dump’ price manipulation. Easterbrook (1986) and Pirrong (1995) examine commodity markets and argue that a sharp rise in the price of a commodity, followed by a fall of similar size, is characteristic of manipulation. Aggarwal and Wu (2006) study U.S. SEC actions in stock manipulation cases and find that prices trend throughout the manipulation period and reverse in the post-manipulation period.

A ‘manipulative short squeeze’ should follow this same general pattern of ‘pump and dump’ but also involves the recall of a stock loan. Consider a situation where a manipulator owns shares in a company and those shares are out on loan to a short-seller. The manipulator wishes to ‘pump up’ the share price and so buys *additional* shares in the company, demanding liquidity from the market. Simultaneously, he recalls the stock that is on loan. If the short-seller is unable to locate new stock to borrow, he must cover his position by buying stock in the open market. The market impact of these purchases places further upwards pressure on the stock price. The short-seller suffers a loss as he covers his position at a price above the initial, undisturbed share price. Finally, the manipulator 'dumps' his shares at the new, higher share price. In so doing, he secures a profit and completes the manipulation process.

A manipulative short squeeze thus combines (at least) two of the three classes of manipulation described by Allen and Gale (1992): trade-based manipulation ('pump and dump') and action-based manipulation (stock loan recall). We refer to the full process as 'pump, squeeze, and dump' and an understanding of this process informs our methodology for detecting such events.

There are considerable practical challenges to researching this topic. Jiang *et al.* (2005) show that it is difficult to use market data to distinguish between manipulations and informed trading. Additionally, stock lending markets are decentralized and publicly available data does not explicitly identify stock loan recalls. Thus, it is not possible to *affirmatively* identify a manipulative short squeeze from public data on stock lending or short-selling – it is only possible to *infer* stock loan recalls from patterns in the data. Even with private data that reveals stock loan recalls, the motivation behind a recall will remain unknown. Mahoney (1999) argues that it is difficult to test for profitable manipulation in actual trading, as manipulation is likely to be disguised. Fischel and Ross (1991) argue that trade based manipulation is often confounded by false statements and fictitious trades, making it difficult to affirmatively identify manipulation from direct questioning of market participants. In light of the practical difficulties in identifying manipulative short squeezes, it is little surprise that this topic is under-researched and poorly understood.

To overcome these problems, we define a pattern of market data with respect to stock returns and total shares on loan that is *consistent* with a manipulative short squeeze. We call such an event an 'apparent manipulative short squeeze'. We describe a set of rules for identifying apparent manipulative short squeezes in the methodology section.[2]

We use a specially gathered set of panel data to investigate manipulative short squeezes with the

[2] Our approach is similar to research into technical analysis, such as tests of technical trading strategies (for example, Hsu & Kuan, 2005; Ready, 2002; Savin et al., 2007) but, in addition, matches trading patterns to underlying stock borrowing activities.

aim examining the frequency and nature of such events, the losses that short-sellers suffer, and the type of stocks affected. We find that manipulative short squeezes are, indeed, rare, but that short-sellers experience permanent losses as a result of short-covering during these events.

Short-sellers can take practical steps to mitigate recall risk, including paying additional fees to borrow on a 'term basis' (i.e. for a fixed period of time) rather than on a call basis (i.e. with repayment of the loan on demand); and borrowing more shares than initially required so as to create a 'buffer' against stock loan recall. Both of these mitigation techniques incur a cost, however. In effect, this creates a trade-off between an indirect constraint (the risk of a manipulative short squeeze) and a direct constraint (the mitigation cost).

This topic is important because the fear of manipulation can constrain short-selling. As short-selling plays an important role in the process of arbitrage and price discovery, such indirect constraints on short-selling can inhibit information from being reflected in a market, thus influencing asset pricing. Nevertheless, this topic remains under-researched, perhaps because of the challenges involved in identifying manipulation.

The remainder of the paper is as follows. In the next section we describe the data we use to investigate manipulative short squeezes. In section 3, we describe our methodology. We then present the results of our tests in Section 4. In the final section we offer some conclusions.

2. Data

2.1 Data Sources

To research this topic, we merge data from two sources. The first of these is a commercial database of U.K. stock lending data from Index Explorers Ltd[3]. This contains daily information on stock lending starting on September 3rd 2003 when the database came into existence. At inception, this database included stocks from the 350 largest companies traded on the London

[3] Index Explorers data has also been used by Saffi and Sigurdsson (2007) and Mackenzie and Hendry (2008).

Stock Exchange. The amount of stock on loan is updated daily, but with a three day reporting lag (before December 12th, 2005 the lag was five days). Over time, the coverage of companies in the database increases through the addition of smaller capitalization stocks so that by the end date for this sample, May 31st 2007, there is stock lending data for 681 companies. The smallest of these companies have market capitalizations of approximately £25 million (approximately U.S.$40 million) as of 2007. A number of companies cease to exist at some point during the 45 months (979 trading days) studied. This could be as a result of a merger or acquisition, the lapsing of the company into administrative receivership, or a change to private ownership. Such companies are included in the database until the date of their de-listing, to prevent survivorship bias. We make use of all stocks in the database and all dates in the sample for which stock lending data is available.

The Index Explorers database includes the following daily information for each stock:

- Date
- Name of company
- SEDOL (a unique company identifier code)
- Turnover (defined as the number of shares traded that day)
- Stock Price (defined as the previous day's closing stock price)
- Volume (defined as turnover multiplied by stock price)
- Market Capitalisation (defined as number of shares in issue multiplied by stock price)
- Shares on Loan (defined as the number of shares reported to CREST as being on loan)
- Volume on Loan (defined as shares on loan multiplied by stock price)
- Percentage of Market Capitalization on Loan (defined as the volume of shares on loan divided by the market capitalization)
- Dividend Record Dates (the dates on which the recorded owners of shares on that day become entitled to receive the next dividend payment)
- Stock Utilisation Rate (the percentage of shares available for borrowing that are actually borrowed)
- Weighted Mean Stock Lending Fees (a weighted average of the fees paid by stock borrowers to stock lenders on initiation of the stock loan, measured as a proportion of the value of shares borrowed).

We use Datastream to obtain stock return data, book value per share, and free float percentage of shares for all the firms in our universe.[4] To facilitate the estimation of abnormal stock returns using an asset pricing model, we collect stock returns data for the year before the start of the Index Explorers database. This 'formation period' runs from September 1st 2002 to September 1st 2003 and is used to estimate the beta of each stock in the study.

Using each company's SEDOL code as a unique identifier to reconcile stocks across the two databases, we merge the two databases to form an unbalanced panel of data for between 350 and 681 companies covering 979 trading days.

2.2 Stock Lending as a Proxy for Short-Selling

Direct data on short-selling is not publicly available in the U.K. Instead, stock lending data is available, on a daily basis. Stock lending acts as a proxy for short-selling, as the process of short-selling generally requires stock to be borrowed to facilitate settlement of the trade.[5] However, there are a number of problems with using stock lending data as a proxy for short-selling.

First, stock does not need to be borrowed to undertake 'naked' short-selling (i.e. short-selling where there is no intention of subsequently settling the trade). This practice is prohibited or actively discouraged in most markets.

Second, stock lending can occur for reasons other than short-selling, including borrowing stock so as to exercise a vote at a firm's General Meeting. Such a strategy would be illegal in the U.S., but it is merely regarded as unethical in the U.K. To prevent this practice, stock lenders are recommended to recall loaned stock prior to voting dates.[6] Another strategy involving stock borrowing is 'dividend tax arbitrage', a strategy that is feasible when a 'borrower' has a tax

[4] Free float percentage of shares is defined as the percentage of the total number of shares of a firm in issue that are available to ordinary investors (i.e. that are not held away from the market by government or close family interests).

[5] Other papers that use securities lending data include D'Avolio (2002), Cohen *et al.* (2007), Saffi and Sigurdsson (2007) and MacKenzie and Henry (2008).

[6] Myners Report, 2001. http://www.hmtreasury.gov.uk/media/DCB/53/myners_principles_web.pdf

advantage over the ‘lender’. Christoffersen *et al.* (2002, 2005) demonstrate increases in securities lending around dividend record dates. To minimize the risk that stock lending for dividend tax arbitrage is confounded with borrowing to facilitate short-selling, we remove data from three weeks before until three weeks after the dividend record date for each stock in this study of stock lending data. This is consistent with the method employed by Saffi & Sigurdsson (2007).

Third, the extent to which market practitioners fail to fulfil their obligations to report stock lending to the market authorities is a further limitation on the use of stock lending data as a proxy for short-selling. Discussions with practitioners involved in stock lending suggest that this problem is rare, but unavoidable.

Finally, derivatives can be used to effect transactions that are economically equivalent to short-selling (see, for example, Ofek *et al*., 2004). The extent to which the use of derivatives to facilitate short-selling is transmitted into the stock lending market influences the usefulness of stock lending data as a proxy for short-selling. Discussions with stock-lending practitioners suggests that the majority, but not all, short-sale-equivalent trades using derivatives are ultimately hedged by the counter-parties to those trades, through borrowing stock and selling short.

2.3 Advantages and Limitations of the Dataset

A number of studies into short-selling make use of monthly data (e.g. Senchack and Starks, 1993 and Dechow *et al.*, 2001, Gamboa-Cavazos and Savor, 2007). However, Christophe *et al.* (2007) criticise the use of monthly short-selling data, as it “represents only a snap-shot of total shorted shares on one day during the month.” Cohen *et al.* (2007) find that almost half the securities lending contracts they study are closed out within two weeks, while the median contract length is 11 days. This suggests that monthly data could be inadequate for understanding the trading practices of short-sellers. This study uses daily data on shares borrowed, and this higher frequency data allows for an appropriate degree of granularity for research into short-selling.

Due to differences in regulatory and institutional frameworks, evidence from studies of U.S. data is not necessarily representative of behaviour outside the U.S. markets. For example, in the U.K., the Financial Services Authority does not impose specific restrictions or controls on short-selling, unlike in the U.S. Instead, short-sellers are subject to general market and regulatory arrangements, including market abuse principles. Furthermore, studying data from outside the U.S. can be used to counter the criticism that observed regularities in empirical studies are simply due to data snooping. A limited number of studies investigate short-selling outside the U.S. (e.g. Aitken *et al.*, 1998, Biais *et al.*, 1999, Poitras, 2002, Ackert and Athanassakos, 2005, Au *et al.*, 2007, Loncarski *et al.*, 2009). However, these studies do not involve an investigation into manipulation, as considered in this paper.

Geczy *et al.* (2002) examines shares available for borrowing (and thus available for shorting), based on a single lender of stock for a twelve month period. D'Avolio (2002) examines an eighteen month period of data from one stock lender. This research contributes to the empirical literature on short selling and manipulation in that it draws on a longer time period than either Geczy *et al.* or D'Avolio, and uses market-wide data on stock lending. In doing so, it adddresses the problem of substitution effects across lenders that might be present in studies based upon a single stock lender.

2.4 Descriptive Statistics

The dataset forms an 'unbalanced panel' dataset in which some cross-sectional units have some of the time periods missing. This form of panel is a result of the number of companies recorded in the Index Explorers database growing over time as smaller capitalization stocks are added. The resulting dataset contains 10,259,946 observations in the overall sample; 6,542,712 of which are non-blank.

In Table 1, descriptive statistics are produced for three points in time: the first day of the sample time period for which all the variables existed (01/09/2003), the last day of the sample time period (31/05/2007), and the mid-point (15/07/2005).

[INSERT TABLE 1 ABOUT HERE]

Further examination of the time series of percentage of market capitalization on loan series for each stock shows that these can be volatile series. Dividend-paying stocks often experience large increases in shares on loan around divided record dates, indicating a dividend capture effect that is consistent with dividend tax arbitrage. Nevertheless, some cross-sections experience a consistently high level through the observed period. During some dates in the sample the maximum value for this series exceeds 100% for some companies, signifying that borrowed shares have been re-lent.

2.5 Asset Pricing Model for Estimating Abnormal Returns

In choosing an asset pricing model for the purposes of calculating abnormal returns, we note that Asquith and Moelbroek (1996) establish that the negative relation between excess returns and short positions is robust to a variety of techniques for calculating excess returns. Dechow *et al.* (2001) measure excess returns by adjusting each firm's return by the equal weighted return for all NYSE and AMEX shares over the same time period. They make no adjustment for risk across firms and cite previous research in this field that has been robust to changes in the asset pricing model used. Figlewski (1981) and Figlewski & Webb (1993) use the CAPM model. Asquith *et al.* (2005) and Boehmer *et al.* (2008) use several asset pricing models to estimate abnormal returns for short-sellers but find no significant difference between the results. Gamboa-Cavazos and Savor (2007) apply both benchmark-adjusted returns approach and Fama-French three factors regression to study the relationship between short selling activities and subsequent abnormal returns, and obtain similar results for both. In fact, results in this research space have been *uniformly robust* to changes in asset pricing model. Noting this, we use the CAPM model for its simplicity and its relevance to practitioners. We use 3-month LIBOR as the risk free rate. LIBOR is commonly used as a risk-free proxy. We note that this series was 'well-behaved' during the period of study, but later became unusually dislocated during the 2007-2009 U.S. and U.K. banking crisis.

3. Methodology

Definition of an 'Apparent Manipulative Short Squeeze'

We draw upon Mahoney's (1999) suggestion that a large abnormal return in the absence of a news announcement, followed by a reversal of similar magnitude (as investors learn that the trading was not information-based) is indicative of manipulation. Furthermore, as we are interested in cases where borrowed stock is recalled and cannot be replaced, we expect to observe a decline in the total shares on loan during the manipulation process.

We seek to identify patterns of stock returns and changes to shares on loan that are *consistent* with the 'pump, squeeze and dump' pattern expected from a manipulative short squeeze. We call this an 'apparent manipulative short squeeze'. Specifically, we identify any situation in which all of the following occur: the stock price rises 'exceptionally' over some limited time period (the 'pump' phase), followed by a fall in the number of shares on loan (the 'squeeze' phase); and subsequently, the stock price reverts towards the original, undisturbed level (the 'dump' phase). Furthermore, these events should not coincide with any regulatory news announcements (these can include trading statements, corporate results, announcement of share buybacks, change of directors, etc.) This latter requirement avoids the confounding of a manipulative short squeeze with reaction to new, public, company-specific information. By requiring that an exceptional price rise is followed by a price reversal, we are able to separate a manipulative short squeeze from 'informed' trading upon private information (a price reversal would not be expected in the latter case). This accords with the Diether *et al* (2009) findings about overreaction in short sales.

We define an 'exceptional' rise in stock price as one that is large relative to the volatility of returns for that stock. We identify stock price rises over a three day period as stock loan recalls in the U.K. are settled in the same way as stock purchases, meaning that borrowers have three working days to return the stock (Faulkner, 2006)[7]. Once a stock loan is recalled, a borrower who has shorted stock has three options: first, he could successfully find replacement stock; second, if unable to successfully find replacement stock, he could delay the return of the stock loan for up to three days in the hope of finding an alternative source of borrowing in this time; third, he could cover his short position immediately and return the stock loan. Thus, even where the 'pump phase' coincides with a stock loan recall, it could take up to three days before the short-seller covers his position. For this reason, we measure the pump phase over three days. For each firm day, we measure the standard deviation of returns for the preceding sixty days. Sixty days is sufficiently long to allow for a meaningful estimate of stock return volatility, but also short enough to avoid becoming 'stale'. By measuring return volatility in this way for each firm day, we take account of the fact that volatility varies over time. We regard an exceptional stock price increase to be one where the stock price rises over any three-day period by at least 2.5 times the standard deviation of daily returns for that stock. Assuming an approximately Normal distribution of stock returns, this method would generally isolate situations that fall within the top percentile of stock price changes.

After receiving an order to return a stock loan, we expect a short-seller will search for alternative sources of borrowing. If a replacement loan is found, the short position need not be covered. However, the U.K. lending market is decentralized and thus finding replacement shares can take time. D'Avolio (2002) observes for his sample of U.S. stocks that when loans are recalled, there is usually no immediate replacement available. Since in the U.K. it takes three days to deliver purchased stock under standard settlement arrangements, some short-sellers might be expected to cover immediately upon loan recall. However, there is another group of borrowers who may prefer to delay covering their positions and look for replacement loans in subsequent days. If unsuccessful and eventually forced to cover, they will have to pay a premium for the delivery of stock to be made in one or two, rather than three days. Moreover, uninformed traders might start taking long positions around the same time, believing that the buyers they observe are informed market participants (Hong and Stein, 2003). On the whole, there is likely to be a lot of noise in the stock price on the days immediately after the recall, but it is realistic to expect that the initial

[7] A typical stock lending agreement in the U.K. requires the return of stock within three days of recall. Failure to return recalled stock within this time entitles the lender to claim costs from the borrower, and to serve a written notice of 'Event of Default', which can have repercussions for the borrower with respect to other counter-parties.

stock price rise will start to reverse by the third day after the stock loan recall. We define the event date (day 0) as the first day following the exceptional rise in share price on which the number of shares on loan falls. We ensure that there are no Regulatory News Service announcements from five days prior to the event date until ten days after the event date. Thus, the observed patterns are not the result of reactions to new, public information.

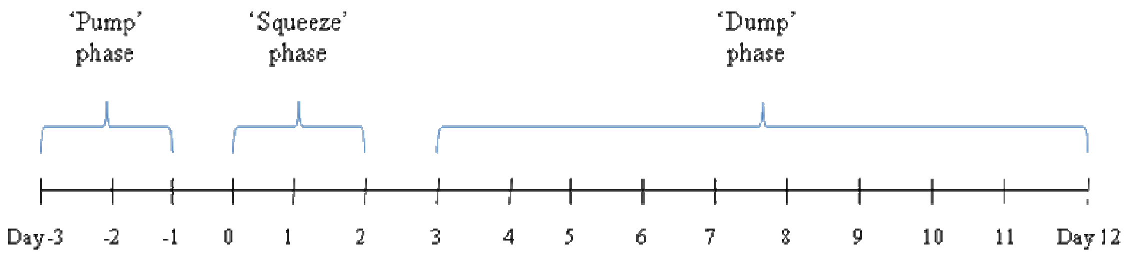
It is not clear over what time period the stock price reversal should take place. Most theoretical models of price manipulation assume complete price reversal, but use ‘notional’ time periods (for example, Aggarwal and Wu, 2006). Thus, we expect complete price reversal over some unknown time period. If we over-estimate the time period, we should expect to observe complete price reversal, but are more likely to introduce confounding influences such as a change in company or economic fundamentals. By under-estimating the time period, we would expect to see partial price reversal only. Without a good theory on the time taken for a stock price to revert fully to its fair value, we prefer to identify partial reversal over a limited time period, as this reduces the risk of confounding factors contaminating the study. We report cases with a price reversal of at least 70% over a ten day period following the event date.

Estimating Abnormal Returns around Apparent Manipulative Short Squeezes

Having identified a number of ‘apparent manipulative short-squeezes’, we then estimate abnormal returns for the stocks involved. As described in Section 2, we use the CAPM model to estimate abnormal returns and employ a one-year formation period to estimate betas.

We estimate abnormal returns for each of the three phases associated with an ‘apparent manipulative short squeeze’. “Phase 1” (the ‘pump’ phase) lasts for three days, from day –3 to –1; “Phase 2” (the ‘squeeze’ phase) also lasts for three days, from day 0 to day 2; and “Phase 3” (the ‘dump’ phase) lasts for ten days, from day 3 to day 12. Figure 2 illustrates these three phases in the form of a timeline.

Figure 2 Timeline Representing the Three Phases of an 'Apparent Manipulative Short Squeeze'



The final step is to calculate how much short-sellers lose during these phases. We calculate average cumulative abnormal returns from the start of the 'pump' phase to the end of the 'squeeze' phase (i.e. from day –3 to day 2). By this time, short covering is expected to be complete, and the short-seller should no longer be exposed to stock price movements. However, during the 'pump' phase (i.e. day -3 to day -1) short-sellers are highly likely to have experienced negative abnormal returns, because by definition stock prices were increasing. Including this interval in the analysis might result in a biased outcome. As a solution to this problem, we adopt an alternative approach that starts to measure cumulative abnormal returns from the event day (day zero) until the end of the squeeze phase (day 2). We then test if these returns are statistically significantly different from zero, by comparing to the relevant 2.5% t-test statistic with degrees of freedom equal to the number of companies in the sample minus one.

4. Results

We observe thirty-six incidences where a stock price rises exceptionally, then shares on loan decreases, followed by a stock price reversal, in accordance with our explanation from Section 3 above. Of the thirty-six 'apparent manipulative short squeezes' identified above, sixteen are associated with regulatory news announcements. We eliminate these, as it is not possible to distinguish between a reaction to a news release and a manipulative short squeeze. This leaves twenty apparent manipulative short squeezes — a small number of incidences to observe over approximately half a million firm days.

We examine the abnormal returns for stocks involved in 'apparent manipulative short squeezes' for each day during the manipulation process (days -3 to 12). We group the companies into portfolios and test the null hypothesis of daily returns being equal to zero. Results are reported in Table 7. Panel A shows the equally-weighted portfolios: returns for these portfolios are significantly different from zero for eight of the 16 days. Panel B shows the market cap-weighted portfolios: only two of the 16 days exhibit returns that are significantly different from zero. The greatest magnitudes for the daily abnormal returns are observed during the pump phase and on the event day. The difference in results between the equally-weighted and market-cap weighted portfolios indicates a more profound effect with smaller firms, consistent with Jiang *et al.*, (2005).

[INSERT TABLE 7 ABOUT HERE]

To consider the potential losses to short-sellers, we estimate the cumulative abnormal returns for each phase of the 'apparent manipulative short squeezes'. Table 8 presents the results: Panel A shows cumulative abnormal returns by phase for the equal-weighted portfolios, and Panel B shows cumulative abnormal returns by phase for the market-cap-weighted portfolios.

[INSERT TABLE 8 ABOUT HERE]

From Panel A, we can reject the hypothesis of zero abnormal returns for the equally-weighted portfolio for each phase. We observe significant positive abnormal returns of 3.45% in the first phase (days –3 to –1) and significant positive abnormal returns of 2.26% in the second phase (days 0 to 2). These positive abnormal returns are followed by significant reversals in the third phase. In Panel B we observe much lower abnormal returns, as a small number of large-cap stock observations have lower abnormal returns but large weights in the portfolio. The positive abnormal returns in phase one and phase two are significant at the 5% level using a one-tailed test. The above results indicate significant losses for short-sellers around apparent manipulative short squeezes.

Table 9 shows cumulative abnormal returns for portfolios by day, rather than by phase, up until the start of the expected price reversal. Panel A shows equally-weighted portfolio cumulative abnormal returns by day. Cumulative abnormal returns peak at 5.91% by day 1 and start to reverse thereafter. We also show the upper and lower thresholds to the 95% confidence intervals for these cumulative abnormal returns. Recall that during days –3 to –1 (the 'pump' phase) short-sellers are highly likely to have experienced negative abnormal returns, because stock prices were increasing. Including this interval in the analysis might result in a biased outcome. Consequently, we adopt an alternative approach in Panel B, and start to measure cumulative abnormal returns from event day (day zero). Cumulative abnormal returns peak at 2.47% on day 1. In Panel C and Panel D, we show the corresponding results for market-cap weighted portfolios. Cumulative abnormal returns peak at day 2, at much smaller magnitudes than those of the equally-weighted portfolios.

[INSET TABLE 9 ABOUT HERE]

The tables above reveal averages for a portfolio of stocks subject to 'apparent manipulative short squeezes'. By examining the underlying data we observe that the maximum loss a short-seller would have suffered from any individual stock was 8.16% in phase one and 13.74% in Phase two. Note that a trader or long-short fund manager would normally hold a number of short positions at any time. Stocks subject to manipulative short squeezes are likely to form a subset of these short positions. When considered in this broader context, the abnormal returns observed above, while statistically significant, are likely to be of moderate economic significance.

Characteristics of Stock Subject to Apparent Manipulative Short Squeezes

In the literature, manipulation is associated with smaller stocks (Jiang *et al.,* 2005); stocks with lower liquidity (Aggarwal and Wu, 2006); elevated volatility of stock returns (Mahoney, 1999) and elevated stock trading volumes (Zhou and Mei, 2003; Aggarwal and Wu, 2006). We examine the characteristics of the stocks in our sample that are subject to apparent manipulative short squeezes. We develop two proxies for liquidity. First, we compare the free float number of shares for each stock with that of the average stock on the event day. Second, we calculate the number of days of normal trading volume that it would take for all short-sellers to cover their positions. This latter is called the 'Days to Cover Ratio' (DCR) and is defined as:

$$\text{Days to Cover Ratio}_{\text{i,t}}\ (\text{DCR}) = \frac{\text{Shares on Loan}_{\text{i,t}}}{\text{Average Daily Trading Size}_{\text{i,t}}} \qquad (2)$$

Where:

$\text{Days to Cover Ratio}_{\text{i,t}}$ is the 'days to cover ratio' for stock *i* on day *t*.

$\text{Shares on Loan}_{\text{i,t}}$ is the closing number of shares on loan for stock *i* on day *t*.

$\text{Average Daily Trading Size}_{\text{i,t}}$ is the moving average of the number of shares traded for stock *i* from days (*t*-61) to (*t*-1). We choose 60 days of trading as a compromise between the risk of including out-of-date information on trading volume and the risk of one or more exceptional days influencing the moving average figure.

A stock with a high days to cover ratio is deemed to be less liquid (from a short-seller's perspective) than a comparable stock with a lower days to cover ratio. For each day during the manipulation period, we compare the DCR of a stock with its average value over the three preceding months. This allows us to observe any trend in this liquidity ratio during the apparent manipulative short squeeze.

We measure the volatility of stock returns for each company that is subject to an apparent manipulative short squeeze, from 20 days prior to the event date through to 10 days after the event date. For each of these days volatility is calculated as the standard deviation of returns for the twenty preceding days.[8] For each firm day, we compare the stock volatility measure to the year's average for that firm.

For each stock subject to an 'apparent manipulative short squeeze', we record trading volume for the five days preceding the start of the manipulation process and compare this to the three month average trading volume for the stock.

Table 12 summarizes the key characteristics (size, volatility, trading volume, liquidity, and utilisation rate) for each stock and for the portfolio of stocks involved in 'apparent manipulative short squeezes'.

[INSERT TABLE 12 ABOUT HERE]

The majority of stocks have market capitalizations of less than one-fifth the market average. This provides some support for the argument that smaller companies are more vulnerable to manipulative short squeezes. However, a small number of large-cap stocks increase the portfolio mean market capitalization, so that it is above the market average. There is some support for the notion that the volatility of returns of stocks is elevated ahead of a manipulative short squeeze – stock volatility as measured at day 0 during an 'apparent manipulative short squeeze' is slightly

[8] The number of days needs to be as small as possible to grasp the changes in volatility that we expect to see around the manipulative short squeeze. Nevertheless, this number still has to be sufficient to calculate reliable standard deviations. I choose 20 days as a compromise between these two requirements.

above its annual average (at 103.2% of annual average), but this result is not statistically significant. The mean trading volume is elevated prior to an 'apparent manipulative short squeeze' compared to its 3 month average, at 123.6% of its 3 month average, but again this result is not statistically significant. The majority of stocks have a free float value of shares less than one-fifth the market average. This supports the view that less liquid stocks are more vulnerable to and more likely to be the target of manipulation. As an alternative measure of liquidity, we examine the number of days of normal trading volume that it takes investors to cover their short positions (The Days to Cover Ratio, or DCR). The portfolio mean DCR at day 0 is 103.4% of its three month average, but this result is not statistically significant. The percentage of shares on loan is not elevated for stocks subject to 'apparent manipulative short squeezes'. In conclusion, there is weak support for the notion that manipulative short squeezes are associated with stocks with smaller market capitalization and free float, elevated trading volume and reduced liquidity.

Using the above observations, we analyse all firms in the dataset to identify stocks that display similar qualities to those found in the set of 'apparent manipulative short squeezes'. Specifically, we identify instances where the market cap and free float value of a company are below the market average, and where the stock's DCR and turnover are above their 60 day average. If a stock has more than one day when it satisfies these conditions, we treat every such occurrence as a separate event. We find 12,909 firm days satisfying the conditions described above. However, there is on average no price response around these occurrences. This suggests that it is difficult to predict a manipulative short squeeze based strictly on these size, trading volume, and liquidity criteria, as many 'false positives' will emerge.

Jacobs and Levy (2007) argue that if a security does become subject to a short squeeze then a reduction in the supply of loanable stock is usually signalled by a decline in the rebate rate offered by prime brokers, or by warnings from the prime brokers, so the position can be scaled back or covered in advance of any demand that borrowed stock be returned. According to this argument, short squeezes are rare and can largely be predicted, posing little threat to short-sellers. We test this argument on our sample by studying stock loan utilization rates (a measure of the proportion of available stock to borrow that is indeed borrowed), and stock loan fees (i.e. cash return – stock loan rebate rate) around the time of the apparent short squeezes. These data are shown in the final four columns of Table 6. We find no evidence that utilization rates, and stock lending fees rise around the time of the apparent manipulative short squeezes. This is not consistent with the argument put forward by Jacobs and Levy (2007). Our findings indicate that it is difficult to predict a manipulative short squeeze using publicly available information. It is perhaps this characteristic — that these are unpredictable events that can have economic impact — that has led to the fear of manipulative short squeezes amongst practitioners.

6. Conclusions

We examine stock lending data for evidence of patterns consistent with manipulative short squeezes. Out of a sample comprising nearly half a million firm days, we identify only 20 'pump, squeeze, and dump' patterns that are unrelated to news-flow. However, where they do occur, short-sellers lose money. We find statistically significant abnormal returns around these events that are also economically significant with an average cumulative stock return of 3.45% in the 'pump' phase, and 2.26% during the 'squeeze' phase. These are followed by a price reversal, but short-sellers who have covered their positions do not benefit from this effect.

There is some (weak) support for the notion that trading volume and the volatility of stock returns is elevated before an 'apparent manipulative short squeeze'. Liquidity is poorer: it takes more days to cover a short position just before the squeeze than on average during the previous three months. However, it is difficult to forecast manipulative short squeezes from this data alone.

Our results provide support for the Jacobs and Levy (2007) assertion that short squeezes are rare events. Nevertheless, we show that short-sellers lose money at such times and that it is difficult to predict short squeezes using market data.

Table 1: Descriptive Statistics

Descriptive statistics are provided for three points in time: the first day of the sample time period (01/09/2003), the mid-point (15/07/2005) of the sample time period and the final day of the sample time period (31/05/2007). The descriptive statistics are parameters that measure central tendency, dispersion, minimum/maximum values, number of observations, skewness, kurtosis and Jarque-Bera statistics for the logarithms of six variables: stock price, market capitalization, percentage of market capitalization on loan, shares on loan, book value per share* and free float number of shares (%).

		Price (GBp)	*Market Cap (mill GBP)*	*Market Cap on Loan (%)*	*Shares on Loan (mill)*	*Book Value per Share (GBP)*	*Free float number of shares (%)*
	Mean	5.316258	6.046764	0.487787	1.834715	0.058888	3.981826
	Median	5.383342	5.739793	0.482426	1.704748	0.188966	4.043051
	Maximum	9.92818	11.46955	2.749192	6.983604	5.227455	4.60517
	Minimum	0.854415	3.850147	-1.89712	-2.302585	-5.521461	2.197225
	Std. Dev.	0.968889	1.50577	0.894732	1.773594	1.258237	0.359823
01/09/2003	***Skewness***	-0.272131	0.993897	0.055387	0.180727	-0.629466	-1.253193
	Kurtosis	5.221265	3.76551	2.824535	2.377743	5.023834	5.077885
	Jarque-Bera	127.7051	93.01533	0.493385	5.93E+00	142.2571	251.7399
	Probability	0.00	0.00	0.78	0.05	0.00	0.00
	Observations	586	492	275	275	601	570
	Mean	5.567265	6.24073	0.880144	2.194331	0.252293	4.333748
	Median	5.583496	5.9428	0.854415	2.140066	0.293037	4.406719
	Maximum	10.07112	11.78012	2.961141	6.764	5.399338	4.60517
	Minimum	1.766442	3.931826	-1.139434	-1.609438	-4.710531	2.397895
	Std. Dev.	0.930843	1.460353	0.873153	1.655141	1.204421	0.266321
	Skewness	-0.215372	1.047292	0.055395	0.071518	-0.387375	-1.963846
	Kurtosis	4.853598	3.923735	2.261525	2.446984	4.299419	9.156942
15/07/2005							
	Jarque-Bera	96.11709	118.1313	7.225814	4.23E+00	59.12548	1391.147
	Probability	0.00	0.00	0.03	0.12	0.00	0.00
	Observations	637	541	311	311	620	626
	Mean	5.899454	6.474853	0.415943	1.239666	0.420813	4.279769
	Median	5.988961	6.137727	0.576613	1.193923	0.439221	4.343805
	Maximum	10.19336	11.60256	3.378611	8.240965	5.578597	4.60517
	Minimum	1.766442	2.995732	-4.60517	-2.302585	-3.963316	2.890372
	Std. Dev.	1.01162	1.495919	1.345159	2.045757	1.20275	0.275389
	Skewness	-0.276713	0.932306	-0.619932	0.144035	-0.147303	-1.485895
	Kurtosis	4.001597	3.59038	3.190487	2.387284	4.254811	5.865685
31/05/2007							
	Jarque-Bera	37.15639	101.8494	43.7971	1.22E+01	31.15017	481.4841
	Probability	0.00	0.00	0.00	0.00	0.00	0.00
	Observations	681	639	668	638	450	678

** For the BV variable the snapshots presented are for the BV shifted.*

Table 2. Abnormal Returns around Apparent Manipulative Short Squeezes

Panel A: Equally-Weighted Portfolio Abnormal Returns

Day	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12
Average	-0.35%	1.47%	2.33%	2.25%	0.21%	-0.21%	-0.94%	-0.90%	-0.62%	-0.83%	-0.80%	-0.37%	-0.95%	-1.03%	-0.28%	-0.18%
Std. Deviation	1.42%	1.20%	1.49%	2.13%	2.34%	1.24%	1.51%	2.23%	1.59%	1.28%	1.44%	1.21%	1.95%	1.17%	1.90%	1.78%
t-stat. (abs.)	1.09	5.47	7.00	4.74	0.40	0.75	2.79	1.80	1.75	2.90	2.50	1.38	2.19	3.94	0.66	0.46
Prob. 2 tails	0.29	0.00	0.00	0.00	0.69	0.46	0.01	0.09	0.10	0.01	0.02	0.18	0.04	0.00	0.52	0.65
Prob. 1 tail	0.15	0.00	0.00	0.00	0.35	0.23	0.01	0.04	0.05	0.00	0.01	0.09	0.02	0.00	0.26	0.32

Panel B: Market Cap-Weighted Portfolio Abnormal Returns

Day	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12
Average	-0.01%	0.08%	0.06%	0.05%	0.00%	0.04%	-0.02%	-0.05%	-0.01%	-0.07%	-0.01%	0.01%	-0.02%	-0.04%	0.00%	-0.01%
Std. Deviation	0.03%	0.23%	0.11%	0.09%	0.03%	0.19%	0.07%	0.17%	0.06%	0.19%	0.06%	0.11%	0.09%	0.11%	0.09%	0.03%
t-stat. (abs.)	1.47	1.55	2.61	2.62	0.65	0.93	1.03	1.29	0.72	1.57	0.60	0.55	0.91	1.64	0.21	0.68
Prob. 2 tails	0.16	0.14	0.02	0.02	0.52	0.36	0.32	0.21	0.48	0.13	0.56	0.59	0.37	0.12	0.84	0.50
Prob. 1 tail	0.08	0.07	0.01	0.01	0.26	0.18	0.16	0.11	0.24	0.07	0.28	0.29	0.19	0.06	0.42	0.25

Table 3 Cumulative Abnormal Returns

Panel A. Equally-Weighted Portfolio Cumulative Abnormal Returns

Phase	1	2	3a	3b
Average	3.45%	2.26%	-4.09%	-6.91%
Std. Dev.	2.63%	3.43%	4.28%	5.17%
t-stat. (abs.)	5.86	2.95	4.27	5.98
Prob. 2 tails	0.00	0.01	0.00	0.00
Prob. 1 tail	0.00	0.00	0.00	0.00

Panel B. Market Cap-Weighted Portfolio Cumulative Abnormal Returns

Phase	1	2	3a	3b
Average	0.13%	0.10%	-0.15%	-0.21%
Std. Dev.	0.31%	0.24%	0.32%	0.36%
t-stat. (abs.)	1.92	1.74	2.12	2.60
Prob. 2 tails	0.07	0.10	0.05	0.02
Prob. 1 tail	0.03	0.05	0.02	0.01

Phase 3 has been shown in two ways: as sub-period 3a (days 3 to 7) and full period 3b (days 3 to 12) to provide greater granularity.

Table 4. Cumulative Abnormal Returns by Day

Panel A: Equally-Weighted Portfolios (starting from day –3)

Day	-3	-2	-1	0	1	2	3
Average	-0.35%	1.12%	3.45%	5.70%	5.91%	5.71%	4.77%
Std. Deviation	1.42%	1.81%	2.63%	2.89%	4.53%	4.39%	4.50%
Std. Error	0.32%	0.40%	0.59%	0.65%	1.01%	0.98%	1.01%
Conf. Int.: Higher Value	0.32%	1.97%	4.68%	7.05%	8.03%	7.76%	6.87%
Conf. Int.: Lower Value	-1.01%	0.27%	2.22%	4.35%	3.79%	3.65%	2.66%

Panel B: Equally-Weighted Portfolios (starting from day 0)

Day	0	1	2	3
Average	2.25%	2.47%	2.26%	1.32%
Std. Deviation	2.13%	3.57%	3.43%	3.61%
Std. Error	0.48%	0.80%	0.77%	0.81%
Conf. Int.: Higher Value	3.25%	4.14%	3.86%	3.01%
Conf. Int.: Lower Value	1.26%	0.79%	0.65%	-0.37%

Panel C: Market-Cap Weighted Portfolios (starting from day –3)

Day	-3	-2	-1	0	1	2	3
Average	-0.01%	0.07%	0.13%	0.19%	0.19%	0.23%	0.21%
Std. Deviation	0.03%	0.21%	0.31%	0.38%	0.38%	0.55%	0.57%
Std. Error	0.01%	0.05%	0.07%	0.09%	0.08%	0.12%	0.13%
Conf. Int.: Higher Value	0.00%	0.17%	0.28%	0.37%	0.37%	0.49%	0.48%
Conf. Int.: Lower Value	-0.02%	-0.03%	-0.01%	0.01%	0.02%	-0.03%	-0.05%

Panel D: Market-Cap Weighted Portfolios (starting from day 0)

Day	0	1	2	3
Average	0.05%	0.06%	0.10%	0.08%
Std. Deviation	0.09%	0.08%	0.25%	0.26%
Std. Error	0.02%	0.02%	0.05%	0.06%
Conf. Int.: Higher Value	0.09%	0.09%	0.21%	0.20%
Conf. Int.: Lower Value	0.01%	0.02%	-0.02%	-0.04%

Table 5. Characteristics of Stock subject to Apparent Manipulative Short Squeezes

Event №	Mkt Cap (at day 0 as % of market average)	Stock Volatility (at day 0 as % of Year Average)	Mean Trading Volume, days -3 to 0 (% of 3m Average)	Free Float (at day 0 as % of Mkt Average)	Mean DCR (days -3 to 0)	DCR (at day 0 as % of 3m Average)	Shares on Loan (at day 0 as % of 3m Average)	Mean Stock Lending Fee (days -3 to 0)	Mean Stock Lending Fee (at day 0 as % of 3m Average)	Mean % Stock Utilisation Rate (days -3 to 0)	Mean Stock Utilisation Rate (at day 0 as % of 3m Average)
1	133.2%	194.8%	176.9%	132.4%	2.5	57.7%	61.2%	10.0	96.9%	6.6	45.3%
2	64.5%	73.1%	87.5%	34.4%	5.7	85.8%	85.9%	15.4	93.2%	11.9	87.9%
3	12.0%	79.3%	337.3%	11.5%	2.5	57.0%	74.2%	59.2	37.4%	3.4	142.4%
4	5.1%	96.9%	3.8%	3.2%	31.9	158.1%	101.8%	61.6	97.2%	37.7	85.1%
5	13.7%	79.2%	26.9%	12.7%	10.2	98.5%	106.5%	59.5	78.7%	3.0	95.6%
6	15.2%	79.8%	28.5%	16.1%	2.0	218.2%	102.0%	28.3	46.0%	0.3	37.2%
7	16.2%	70.0%	290.8%	16.3%	1.2	82.1%	84.7%	222.1	81.2%	1.0	107.1%
8	5.6%	243.6%	40.5%	5.7%	24.6	106.1%	127.2%	-	-	-	-
9	73.9%	124.8%	112.9%	69.3%	1.3	52.4%	66.4%	35.8	239.3%	2.3	51.7%
10	31.6%	81.8%	77.6%	23.6%	2.7	110.2%	111.7%	-	-	-	-
11	82.6%	70.9%	97.4%	81.0%	3.0	122.8%	118.9%	19.7	87.8%	10.6	96.8%
12	11.3%	90.2%	76.6%	9.3%	11.1	122.6%	110.5%	-	-	-	-
13	22.5%	101.8%	282.7%	18.7%	9.2	159.3%	109.1%	21.6	133.0%	19.6	113.5%
14	18.5%	147.0%	98.5%	18.4%	3.9	83.4%	100.2%	-	-	-	-
15	13.8%	66.5%	112.6%	10.3%	1.5	82.8%	54.1%	-	-	-	-
16	444.8%	114.7%	80.8%	513.7%	5.6	76.9%	68.3%	10.0	111.2%	6.3	71.8%
17	11.1%	103.6%	101.4%	8.4%	4.2	-	-	-	-	-	-
18	76.5%	71.6%	126.0%	77.8%	12.2	94.9%	95.6%	10.5	76.3%	29.3	89.0%
19	1860.6%	112.5%	163.9%	2154.0%	3.8	91.9%	98.9%	13.6	-	0.1	-
20	27.9%	62.7%	150.4%	27.4%	5.0	-	-	-	-	-	-
Mean	147.0%	103.2%	123.6%	162.2%	7.2	103.4%	93.2%	43.6	98.2%	10.2	85.3%
St. Dev	414.9%	45.9%	89.8%	482.1%	8.0	41.6%	21.0%	57.1	51.3%	11.9	30.2%

References

Ackert, L.F. and Athanassakos, G., 2005. The Relationship between Short Interest and Stock Returns in the Canadian Market. *Journal of Banking and Finance*, 29, 1729-1749.

Aggarwal, R.K. and Wu, G., 2006. Stock Market Manipulations. *Journal of Business*, 79, 1915-1953.

Aitken, M.J., Frino, A., McCorry, M.S., and Swan, P.L., 1998. Short Sales are Almost Instantaneously Bad News: Evidence from the Australian Stock Exchange, *Journal of Finance*, 53 (6), 2205-2223.

Allen, F. and Gale, D., 1992. Stock Price Manipulation. *Review of Financial Studies*, 5, 503-529.

Asquith, P. and Meulbroek, L., 1996. An Empirical Investigation of Short Interest. Working Paper No. 96-012, Harvard University.

Asquith, P., Pathak, P.A. and Ritter, J.R., 2005. Short Interest, Institutional Ownership and Stock Returns. *Journal of Financial Economics*, 78, 243-276.

Au, Andrea S., Doukas, John A. and Onayev, Zhan, 2007. Daily Short Interest, Idiosyncratic Risk, and Stock Returns. Working Paper (November, 2007).

Biais, B., Bisiere, C. and Decamps, J., 1999. Short Sales Constraints, Liquidity and Price Discovery: An Empirical Analysis on the Paris Bourse. *European Financial Management*, 5, 395-409.

Boehmer, E., Jones, C.M. and Zhang, X., 2008. Which Shorts are Informed? *Journal of Finance*, 63 (2), 491-527.

Christoffersen, S.E.K., Geczy, C.C. and Musto, D.K., 2005. Crossborder Dividend Taxation and the Preferences of Taxable and Non-taxable Investors: Evidence from Canada. *Journal of Financial Economics*, 78 (1), 121-144.

Christoffersen, S.E.K., Reed, A.V., Geczy, C.C. and Musto, D.K., 2002. The Market for Record-Date Ownership. EFA 2002 Berlin Meetings Presented Paper. Available at SSRN: http://ssrn.com/abstract=302522

Christophe, S.E., Ferri, M.G. and Angel, J.J., 2007. Should Owners of NASDAQ Stocks Fear Short-Selling? *Journal of Portfolio Management*, 33 (3), 122-131.

Cohen, L., Diether, K.B. and Malloy, C.J., 2007, Supply and Demand Shifts in the Shorting Market. *Journal of Finance*, 62 (5), 2061-2096.

D'Avolio, G., 2002. The Market for Borrowing Stock. *Journal of Financial Economics*, 66, 271-306.

Dechow, P.M., Hutton, A.P., Meulbroek, L., and Sloan, R.G., 2001. Short Sellers, Fundamental Analysis, and Stock Returns. *Journal of Financial Economics*, 61, 77-106.

Diether, K.B., Lee K.H., and Werner, I.M., 2009. Short-Sale Strategies and Return Predictability. *Review of Financial Studies*, 22(2), 575-607.

Duffie, D., Garleanu, N. and Pedersen, L.H., 2002. Securities Lending, Shorting, and Pricing. *Journal of Financial Economics*, 66 (2-3), 307-339.

Fama, E., and French, K., 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33, 3-56.

Figlewski, S. and Webb, G.P., 1993. Options, Short Sales, and Market Completeness. *Journal of Finance*, 48, 761-777.

Figlewski, S., 1981. The Informational Effects of Restrictions on Short Sales: Some Empirical Evidence. *Journal of Financial and Quantitative Analysis*, 16, 463-476.

Fischel, D.R. and Ross, D.J., 1991. Should the Law Prohibit "Manipulation" in Financial Markets? *Harvard Law* Review, 105, 503-553.

Gamboa-Cavazos, M, and Savor, P., 2007. Holding on to your Shorts: When do Short-Sellers Retreat? Harvard University Working Paper.

Geczy, C.C., MU.S.to, D.K., and Reed, A.V., 2002. Stocks are Special Too: an Analysis of the Equity Lending Market. *Journal of Financial Economics*, 66, 241-269.

Gencay, R., 1998. The Predictability of Security Returns with Simple Technical Trading Rules, *Journal of Empirical Finance*, 5, 347-359.

Hong, H. and Stein, J.C., 2003. Differences of Opinion, Short-Sales Constraints and Market Crashes. *The Review of Financial Studies*, 16 (2), 487-525.

Hsu, P-.H. and C.-M. Kuan, 2005. Reexamining the Profitability of Technical Analysis with Data Snooping Checks, *Journal of Financial Econometrics*, 3, 606-628.

Jacobs, B.I. and Levy, K.N., 2007. 20 Myths about Enhanced Active 120-20 Strategies. *Financial Analysts Journal*, 63 (4), 19-26.

Jiang, G., Mahoney, P.G. and Mei, J., 2005. Market Manipulation: A Comprehensive Study of Stock Pools. *Journal of Financial Economics*, 77, 147-170.

Khwaja, A.I., and Mian A. 2005. Unchecked Intermediaries: Price Manipulation in an Emerging Market. *Journal of Financial Economics*, 78 (1), 203-241.

MacKenzie, M. and Henry, Ó.T., 2008. The Information Content of Trading Volume and Short-Sales. Working Paper, Cambridge University.

Mahoney, P.G., 1999. The Stock Pools and the Securities Exchange Act. *Journal of Financial Economics*, 51, 343-369.

Ofek, E., Richardson, M. and Whitelaw, R.F. 2004. Limited Arbitrage and Short Sale Restrictions: Evidence from the Options Market. *Journal of Financial Economics*, 74, 3-5-342.

Pirrong, S.C., 1995. The Self-Regulation of Commodity Exchanges: the Case of Market Manipulation. *Journal of Law and Economics*, 38, 141-206.

Poitras G., 2002. Short Sales Restrictions, Dilution and the Pricing of Rights Issues on the Singapore Stock Exchange. *Pacific-Basin Finance Journal*, 10, 141-162.

Saffi, P.A.C. and Sigurdsson, K., 2007. Price Efficiency and Short-Selling. Working Paper, London BU.S.iness School (10/12/2007).

Savin, G., P. Weller, and J. Zvingelis, 2007. The Predictive Power of "Head-and-Shoulders" Price Patterns in the U.S. Stock Market, *Journal of Financial Econometrics*, 5, 243-265.

Senchack, A.J. and Starks, L.T., 1993. Short-Sale Restrictions and Market Reaction to Short-Interest Announcements. *Journal of Financial and Quantitative Analysis*, 28 (2), 177-194.

Zhou, C. and Mei, J., 2003. Behaviour-Based Manipulation. Working Paper 03028, NYU Stern School of Business.